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Procedia CIRP 67 (2018) 227 – 232

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11th CIRP Conference on Intelligent Computation in Manufacturing Engineering - CIRP ICME '17

Optimization of process parameters for powder bed fusion additive manufacturing by combination of machine learning and finite element method: A conceptual framework

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Abstract

In addition to prototyping, Powder Bed Fusion (PBF) AM processes have lately been more widely used to manufacture end-use parts. These changes lead to necessity of higher requirements to quality of a final product. Optimization of process parameters is one of the ways to achieve desired quality of a part. Finite Element Method (FEM) and machine learning techniques are applied to evaluate and optimize AM process parameters. While FEM requires specific information, Machine Learning is based on big amounts of data. This paper provides a conceptual framework on combination of mathematical modelling and Machine Learning to avoid these issues.

Keywords: Additive Manufacturing; Polymer Powder Bed Fusion; Modeling; Artificial Neural network; Optimization; Material Parameters; Process Parameters.

1. Introduction

Additive Manufacturing (AM) is “process of joining materials to make parts from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing and formative” [1]. Development of new processes and materials provides a wider variety of areas for applications of AM. Nowadays, additive manufacturing is used not just in aerospace, medical and automotive industries but also in fashion, food industry, jewelry production and architecture, etc. [2]. With more use, more needs and requirements are set to products fabricated by additive manufacturing. One of the most difficult issues that should be addressed is how to improve and control quality of as-built part and define what significantly influence the quality level of a part.

Every additive manufacturing process has its own process parameters that in combination with material properties and environmental conditions influence quality of fabricated parts. Experimentally through the observation, it is very difficult to define those parameters and their combinations, which have the most impact on engineering (mechanical, physical and material) properties of the product. In addition, by the reason that practical experiments are expensive (especially for metal powder) [2], detecting parameters that influence quality of as-built part becomes more challenging task.

However, several studies can be found in the literature on application of Design of Experiments (DoE) methods (e.g. Taguchi, half-factorial design, central composite design, etc.) and analysis of variance (ANOVA) to define which parameters and their combination influence which type of properties of the as-built part [3-5].

Since statistical methods require big amount of data for more accurate results, just a few attempts were made comparing with general scientific attention to additive manufacturing. In addition to aforementioned studies focused on Taguchi, ANOVA and DoE methods, Garg, et al. [6] analyzed existing literature on application of empirical modelling for three AM processes (Stereolithography (SA), Selective Laser Sintering (SLS), and Fused Deposition Modeling (FDM)).

On the one hand, finite element modeling (FEM) is in most cases used for numerical solutions of mathematical models and parameters’ optimization, but this process requires deep knowledge on physical properties of material and in-depth understanding of AM process [7]. On the other hand, machine learning techniques can help to predict process parameters, thus avoiding the abovementioned

doi:10.1016/j.procir.2017.12.204

requirements for FEM. Although these techniques normally require big amounts of data for better generalization and accuracy.

Combination of FEM and machine learning can provide possibility to simulate process (FEM), predict or optimize process parameters to achieve desired mechanical properties (Machine Learning), and then test predicted process parameters by testing them on developed models for process simulation (FEM).

Therefore, conceptual framework on combination of statistical analysis, mathematical modeling and machine learning techniques is proposed in this article.

2. Additive Manufacturing

2.1. Powder Bed Fusion Additive Manufacturing

According to ISO/ASTM52900-15 [1], powder bed fusion is "additive manufacturing process in which thermal energy selectively fuses regions of a powder bed". This type of AM processes is widely used to manufacture parts and therefore, more research activities are focused on the improvements of the product properties (physical, material and mechanical properties). The schematic representation of powder bed fusion AM process is showed on Figure 1.

Additive manufacturing process always starts with machine preheating (up to 4 hours). Then process of powder solidification is performed by focusing laser on powder bed to fabricate one layer of designed part (Figure 1). Then powder bed moves down with a step of one layer thickness. The sequence of events should be repeated as many times as needed to build a part. After build is finished, machine should cool down before anyone can open the build chamber to take build cake out from it.

Metallic, ceramic, composite and polymer are types of material that can be fabricated by powder bed fusion additive manufacturing process. In addition, for metallic material, there are also 2 types of fusion source, which are electron beam and laser beam.

By the reason that during last decade more attention is paid to additive manufacturing and its development, there exist enormous amount of published literature about AM and powder bed fusion processes group. Therefore, this article is focused solely on polymer powder bed fusion (PPBF) process. However, other processes from this group should be investigated in the future work.

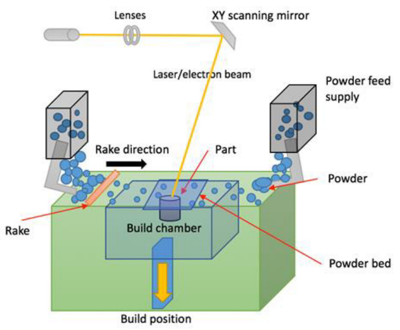

Fig. 1 Schematic representation of powder bed fusion process.

2.2. Application of statistical analysis to define significance of PPBF process parameters

Although there has been relatively little research on what AM process parameters are significant regarding final product quality, several studies reported results of statistical analysis for some AM process parameters. These attempts are based on application of such methods as Taguchi, ANOVA and regression modelling [6, 8, 9].

Singh and Prakash [10] planned experiment by application of two level factorial design of experiment (DOE) and evaluated which AM process parameters have significant impact on part density. Their analysis showed that among such parameters as laser power, scan spacing and scan velocity, the most significant is laser power. Based on ANOVA analysis, regression model was proposed including all significant factors and combinations of all three process parameters. Predicted density is in a good agreement with earlier published results [10].

Mousa [11] investigated influence of five process parameters on shrinkage phenomenon for glass bead-filled polyamide 12 samples fabricated by selective laser sintering. Application of DOE, Taguchi, S/N analysis and ANOVA methods led to the next results: powder base thickness has the most significant impact on shrinkage effect among such parameters as part bed temperature, laser power, powder base thickness, layer cooling time and filler ratio [11]. However, relationship between considered process parameters was not taken into account.

In addition, statistical analysis could be used for optimization and model development. Singh, et al. [12] presented study that is a good example of such application of statistical analysis. They optimized values of laser power, layer thickness, scan speed, and hatch spacing to achieve the best compressive strength without compromising porosity of open porous scaffold, which are fabricated from polyamide 12 by selective laser sintering process [12]. By application of ANOVA method, the authors were able to find regression model on the one hand, and evaluate significance of each parameter and their combination on the other hand. Laser power, layer thickness, hatch spacing and interaction between hatch spacing and laser power contributes the most to the value of compressive strength of scaffolds [12]. Based on the resulting regression model from ANOVA analysis, Singh, et al. [12] used trust region algorithm for parameters optimization. They validated results by fabricating and testing human skull, and comparing obtained results with the simulated one.

In addition, it is worth to mention that results from statistical analysis are also used to develop new mathematical description of powder bed fusion process.

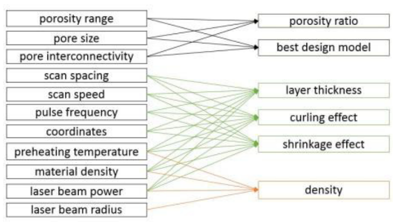

Fig. 2 Example of process and material properties used in mathematical models for analysis of polymer powder bed fusion process [13-15].